EFFICIENCY AND ENVIRONMENTAL FACTORS IN THE US ELECTRICITY TRANSMISSION INDUSTRY

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Abstract

The electricity industry in most developed countries has been restructured over recent decades with the aim of improving both service quality and firm performance. Regulated segments (e.g. transmission) still provide the infrastructure for the competitive segments and represent a significant share of the total price paid by final customers. However there is a lack of empirical studies that analyse firms' performance in the electricity transmission sector. In this paper an empirical analysis of US electricity transmission companies is conducted for the period 2001-2009. We use alternative stochastic frontier models that allow us to identify the determinants of firms' inefficiency. These models also permit us to control for weather conditions, potentially one of the most decisive uncontrollable factors in electricity transmission. Our results suggest that weather conditions clearly have an influence on transmission costs and that there is room for improvement in the management of US electricity transmission systems. Regulators should also be aware that more adverse conditions generate higher levels of inefficiency, and that achieving long-term efficiency improvements tends to worsen firms' short-term relative performance.

Keywords: US electricity transmission; heteroscedastic stochastic frontier models; inefficiency determinants; weather conditions.

JEL classification: D22, L51, L94

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1. Introduction

The electricity industry in most developed countries has been restructured over recent decades with the aim of reducing costs, improving service quality and encouraging electric utilities to perform efficiently. As a result, former state-owned utilities have been privatized and there has been vertical separation of the generation, transmission, distribution and retailing segments, particularly in Europe (see Jamasb and Pollitt, 2005). Some of these segments, such as generation and retailing, have been opened to competition, while other segments such as transmission and distribution are still regulated. However, incentive-based regulation schemes have been implemented in several countries (e.g. UK, Norway) in order to encourage both transmission and distribution utilities to perform efficiently.

Much of the research in the electricity industry has focused on competitive wholesale markets, although the regulated segments provide the infrastructure for the competitive segments and even though networks constitute a significant share of the final price paid by electricity consumers (Joskow, 2014).[1] Even though electricity transmission is necessary for distribution and retailing, there is a lack of empirical studies that analyse both the economic characteristics of the technology and firms' performance in that segment.

Statistical benchmarking methods have been largely used in the electricity industry to determine the relative efficiency of individual firms' costs compared to their peers (see Haney and Pollitt, 2009, 2013). Obtaining reliable (and fair) measures of firms' inefficiency requires controlling for the different environmental conditions under which each firm operates. This is especially acute in benchmarking because of the financial implications that this analysis can have on the firms. One of the most interesting issues with environmental conditions is the question of whether firms are using them as an excuse for poor performance. In line with this, Nillesen and Pollitt (2010) find that firms which operate in unfavourable conditions can be best-practice for the case of US electricity distribution.

One of the most decisive uncontrollable factors in electricity transportation (i.e. transmission and distribution) is the weather conditions of the area in which the companies operate. Billinton and Wenyuan (1991), and Billinton and Acharya (2005) tried to explain changes in the probability of failure rate in the system using engineering models. Generally speaking, they pointed out that most technical interruptions occur when weather is adverse and, in particular, extremely adverse. They also showed that assessing likely failure rates while ignoring weather tends to give erroneous predictions which are too optimistic.

Regarding electricity transmission, Billinton and Wu (2001) pointed out that overhead transmission lines are exposed to a wide range of weather conditions. Moreover, both failures rates and the probability of overlapping failures tend to increase sharply during periods of extremely adverse weather conditions. Rothstein and Halbig (2010) find that many atmospheric and hydrological parameters not only affect electricity generation and consumption, but also electricity transportation. Indeed, overhead lines are affected by several atmospheric influences, such as lightning, wind, additional weight (e.g. ice or snow), low temperatures, humidity and moisture.

[1] Typically distribution and transmission charges combined compose around 25% of the residential bill (excluding taxes and environmental charges).

Despite the potential role of weather conditions in electricity transportation, only a few papers have analysed firms' performance in the electricity distribution sector controlling for environmental factors. In particular, Yu *et al.* (2009) showed using nine weather variables that severe weather conditions tend to increase service interruptions, and this in turn increases costs associated with replacing the damage equipment and restoring power. Jamasb *et al.* (2010 and 2012) also concluded that the lack of inclusion of variables related to weather conditions might downward bias the estimated coefficients of other relevant variables, and, in particular, those associated with the marginal cost of quality improvements. Using weather and geographic composites, Growitsch *et al.* (2012) predicted up to 30% lower costs than average, for utilities that operate in areas with extremely good environmental conditions, and up to 39% higher costs than average, for utilities that operate in areas with extremely bad environmental conditions. On average, they predicted higher costs of about 5% as a result of hostile weather conditions.[2] More recently, Orea *et al.* (2015) advocate the use of supervised dimension reduction methods such as Sliced Inverse Regression (SIR) in efficiency analyses of electricity distribution firms. The use of this type of approach avoids dimensionality problems when the number of weather variables to be incorporated in the empirical models is large.

On the other hand, as far as we are aware there are only five published papers that separately study the performance of transmission firms. None of them includes inefficiency determinants and only the most recent of them has controlled for environmental conditions. Using a sample of US firms, Pollitt (1995) analysed differences in efficiency between state-owned and private electricity transmission companies. He did not find significant differences between both types of firms using parametric and nonparametric specifications of the frontier model. Using also US data, Huettner and Landon (1978) and Dismukes *et al.* (1998) have examined the existence of returns to scale in the provision of electric transmission services. Huettner and Landon (1978) do not find increasing returns to scale, except for one category of sales expenses. By contrast, Dismukes *et al.* (1998) find significant economies of scale for all the NERC (North American Electric Reliability Corporation) reliability regions using data for the period 1986-1991. von Geymueller (2009) carried out a comparison of static and dynamic DEA (Data Envelopment Analysis) models in electricity transmission using data of 50 US utilities for the period 2000-2006. The author finds that static models tend to overestimate firms' inefficiency because they do not take into account the existence of quasi-fixed inputs. Recently, Llorca *et al.* (2014) propose using a Latent Class Model (LCM) approach to control for technological (or environmental) differences when DEA is applied in a regulatory context of electricity networks. In addition to a simulation exercise, the proposed procedure is illustrated with an application to the US electricity transmission industry.

Our paper contributes to the literature analysing firms' performance in the electricity transmission industry with an empirical analysis of US electricity transmission systems for the period 2001-2009. The analysis of the economic characteristics of the technology and the inefficiency of each utility relies on the estimation of several specifications of heteroscedastic models taken from the recent Stochastic Frontier Analysis (SFA) literature. Unlike previous papers, our SFA models allow us to identify the determinants of firms' inefficiency in this industry, and discuss whether the environmental factors should be treated as determinants of firms'

[2] By contrast, Nillesen and Pollitt (2010) find that the best performing US electricity distribution companies do not correlate with unfavourable conditions.

performance or as part of the technology.[3] This is not simply a semantic point within an incentive regulation framework because the indirect effect (through firms' inefficiency) is likely less difficult to mitigate than a direct effect (through the cost frontier) that is independent from firms' relative performance given the nature of the technology. To examine this issue we have applied a modified version of the 'zero inefficiency stochastic frontier model' recently introduced by Kumbhakar *et al.* (2013). To the best of our knowledge, this is the first time this model has been used to capture differences in technology instead of differences in performance.

The estimated coefficients provide useful information about the firms' performance with both policy and managerial implications. We find using more recent data and larger firms than in previous papers that, given network infrastructure, most electricity transmission networks exhibit natural monopoly characteristics. Our results also indicate that more adverse conditions generate higher costs, mainly through higher levels of inefficiency. Furthermore, we find that investing in capital is an effective strategy to deal with adverse weather conditions. On the other hand, we find that, as expected, firms' performance improves when demand tends to be steady as firms cannot adjust their inputs without cost over time. The average efficiency at the beginning of the period is larger than in previous studies. But, using our preferred estimated model, the results indicate that efficiency has declined and diverged over time. This suggests that there is room for improvement in the performance of the US electricity transmission system. It should be mentioned that the use of US data to benchmark European and Australasian utilities is often suggested and has been undertaken by some regulators including the British energy regulator, Ofgem. Hence although the results obtained here relate to US transmission network, they are important for non-US regulators.

This paper is organized as follows. Section 2 provides a brief review of the transmission and distribution literature and the most commonly used approaches to benchmark firm performance in incentive regulation schemes. Section 3 describes the theoretical cost function that we estimate as well as the empirical specifications of the estimated models. Section 4 presents the data and variables used in the empirical analysis. Section 5 reports the parameter estimates and the results obtained from those estimates. Section 6 presents the main conclusions.

2. Benchmarking in electricity transmission

The electricity sector is an industry with different and interrelated activities, which are affected by production and consumption decisions across the whole system. The US electricity system traditionally has been composed of large vertically integrated utilities. Nevertheless, in the last two decades several reforms have been implemented with the aim of disaggregating most utilities into differentiated segments. These reforms have led to different treatments of the separated activities: generation and retail are regarded as potentially competitive markets, while transmission and distribution networks are treated as natural monopolies that have to be regulated (see Joskow, 2014). As Jamasb and Pollitt (2007) point out, from an economic perspective, the aim of electricity unbundling is to provide utilities with incentives to improve their operating

[3] An additional contribution of the present paper is that we control for weather characteristics by including a set of weather variables as determinants of firms' inefficiency. The data was gathered specifically for the present application. In addition, as our sample period is more recent than those analysed in previous papers we can see whether there has been an improvement in average efficiency in the US electricity transmission industry.

and investment efficiency and to ensure that consumers benefit from the efficiency gains. The main methods used to achieve these objectives are incentive regulation mechanisms, which include financial rewards and penalties for the firms linked with their performance.

Joskow (2014) notes that much of the research in the electricity sector has focused on the competitive segments of the system. However, the regulated segments provide the infrastructure for the competitive segments and represent an important amount of the total price paid by final consumers. Moreover, these segments have a significant joint effect along with competitive segments on social welfare. For these reasons, electricity transmission has played an important role in the success of liberalised power markets. Electricity reforms have led to the creation of some bodies to perform the coordination functions that formerly were internal to the firms. To deal with this issue and the stresses in the transmission system after years of underinvestment, the Federal Energy Regulatory Commission (FERC) pursued the implementation of a Standard Market Design in the US. It has also promoted the creation of the so-called Regional Transmission Organizations (RTO) to facilitate efficient trade over wide areas and transmission investment. As Greenfield and Kwoka (2011) note, the RTOs - such as PJM - provide transmission services but do not own transmission facilities. They are also not responsible for the maintenance and repair, or fixed investment costs, of the transmission facilities over which they direct the flow of power. Their essential role is as an independent service provider that administers the terms and conditions of transmission services and maintains the short-term reliability of the network.

Despite the importance of RTOs in the overall performance of the electricity system, the transmission utilities and the structure of the network charges have a great effect on network use and its development. Following Brunekreeft *et al.* (2005, p.74-75), the setting of the charges at an appropriate level is a key issue because it affects "the locational choices of new generation (and of energy intensive users), as well as influencing the bidding behavior of generators, and the willingness of neighboring electricity markets to trade and cooperate". As a result, "ideally the structure of network charges should encourage: *i*) the efficient short-run use of the network (dispatch order and congestion management); *ii*) efficient investment in expanding the network; *iii*) efficient signals to guide investment decisions by generation and load (where and at what scale to locate and with what choice of technology-base-load, peaking, etc.); *iv*) fairness and political feasibility, and *v*) cost-recovery" (Brunekreeft *et al.*, 2005, p.75). There are different regulatory practices across the world to set the total amount of network charges in the electricity market that are mostly based on benchmarking (see Haney and Pollitt, 2013). This implies that firms' efficiency is obtained through comparing each firm to those with best performance. As regulators reward or punish firms according to their (in)efficiency level, the reliability of these scores is particularly crucial for regulatory credibility. Any efficiency estimate tries to measure the gap between actual cost (production) and the optimal point on the cost (production) frontier, which must be estimated from the available data. Published papers have basically employed parametric (e.g. SFA), nonparametric (e.g. DEA), and semi-parametric (e.g. StoNED, Stochastic Nonparametric Envelopment of Data)[4] techniques to estimate cost (production) frontiers. As all techniques have their advantages and disadvantages,[5] the

[4] These models are also labelled as semi-nonparametric.

[5] For instance, SFA has advantages over DEA when noise is a problem, and this can arise from measurement errors or other sources of statistical noise such as luck, weather, equipment failure or similar factors that are beyond firms' control.

selection of an appropriate estimation method is contentious and may influence the obtained results and the consequent regulatory policy implications (see, for instance, Coelli *et al.*, 2005).

Despite the relevance of transmission networks in the electric power industry it is very difficult to implement a statistical benchmarking for most of the countries due to the lack of domestic comparators (Haney and Pollitt, 2013). International benchmarking can be an alternative to deal with this issue, but the regulators face several problems. Joskow (2014, pp.54-55) notes that the layout of the transmission network depends on countless factors, such as "the distribution of generators and load, population density, geographic topography, the attributes and age of the legacy networks' components and various environmental constraints affecting siting of new lines, transformers and substations". Moreover, there is no standardization or homogeneity among countries about the voltage boundaries between transmission and distribution networks. For instance, in the UK the transmission network is mostly formed by elements that run at 275 kV and above, while in other countries like the US or France transmission network is formed by elements that run above 60 kV, making an international comparison a challenging task. Regarding the inputs and outputs that should be taken into account in an empirical analysis on efficiency of transmission systems, Pollitt (1995) pointed out that it might be desirable to take every specific factor of the company into account due to the complexity of the network. Each transmission system is unique because of the different kinds of inputs that they use and the environment in which they operate.

It should be highlighted that this paper is only focused on the US electricity transmission industry, which should be distinguished from electricity distribution. The joint objective of both industries is the transportation and delivery of electrical energy from electricity generation facilities to the end users. However, there are differences between both types of network. The electricity transmission network is composed of high voltage lines that carry electricity over long distances, from bulk power generation facilities to substations that serve sub-transmission or distributions systems (Brown, 2002). On the other hand, distribution systems operate at lower voltages and represent the final stretch of the electric grid that directly connects to final consumers. As the technological characteristics of the transmission grid (e.g. pylons, transmission substations or high-voltage power lines) are different from those of the distribution network (e.g. distribution feeders or pole-mounted distribution transformers), regulating both networks does not involve the same set of inputs, outputs and environmental conditions. In particular transmission lines, are more vulnerable to weather effects and hence the particular relevance of this study. It is also the case that there have been many studies of electricity distribution efficiency, because there are usable national samples of electricity distribution firms in many countries. By contrast, there is only one electricity transmission company in many countries and hence US data of the type used in this study provides one of the few opportunities for analysing a national sample of transmission data globally. That said there are clearly similarities between the efficiency analysis of electricity distribution and transmission; both involve a number of outputs which seek to capture energy flow, peak demand and network size, and a similar conception of input costs.

Statistical benchmarking methods have been widely used in electricity distribution. These methods are applied to determine the relative efficiency of individual firms' operating costs and service quality compared to their peers.[6] Some countries such as Germany, Nordic countries and Switzerland have a large number of utilities. This provides a suitable basis for the use of advanced benchmarking techniques and without necessarily having to recourse to international benchmarking. It is generally desirable for regulators to have a large number of utilities for comparison and efficiency benchmarking.

As mentioned above, obtaining reliable and fair measures of firms' inefficiency requires controlling for the different environmental conditions under which each utility operates. This is especially acute in benchmarking because of the financial implications that this analysis can have over the firms and their effect over the whole network. The concern about the inclusion of environmental variables (also called contextual variables or *z*-variables) has generated the development of several models either using parametric, nonparametric or semi-parametric techniques. Although we do not pretend to provide a complete survey of the alternatives for including *z*-variables, in Figure 1 we present a brief summary of some of the models that can be applied.[7] Given the wide range of models that have been developed, here we only mention the methods most frequently applied.

[Insert Figure 1]

The inclusion of environmental variables in DEA has been done in one, two or even more stages. Ruggiero (1996) and other authors have highlighted that the one-stage model introduced in the seminal paper of Banker and Morey (1986) might lead to bias. To solve this problem, other models using several stages have been developed in the literature. Ray (1988) was the first who proposed a second stage where standard DEA efficiency scores were regressed on a set of contextual variables. This practice was widespread until Simar and Wilson (2007) demonstrated that this procedure is not consistent because the first-stage DEA efficiency estimates are serially correlated. Although the bootstrap procedure proposed by these authors to solve this problem in two stages became a widely used method in DEA to identify inefficiency determinants, three-stage models have also been developed (see, for instance, Fried *et al.* 2002; and Muñiz, 2002).

In the recently developed semi-parametric literature, we could mention three types of models. The first one is the extension of the StoNED method developed by Johnson and Kuosmanen (2011) where the *z*-variables are incorporated additively to the parametric part of the function, which is estimated jointly with the nonparametric frontier. Kuosmanen (2012) has recently applied this approach for the case of the electricity distribution sector in Finland.[8] Alternatively, Li *et al.* (2002) introduced the Semiparametric Smooth Coefficient Model (SPSCM) where the regression coefficients are unknown functions, which depend on a set of contextual variables. Sun and Kumbhakar (2013) extend this model by allowing the environmental variables to also enter through the inefficiency. Finally, the use of an LCM approach allows the identification of different technology parameters for different groups of firms that share environmental features. In an LCM the *z*-variables enter in non-linear form in the probabilities of belonging to the classes, and hence they can be viewed as a "discrete,

[6] Jamasb and Pollitt (2001) show the most used approaches and provide a survey of benchmarking studies applied mainly in OECD countries. For a more current review of applied papers on electricity distribution see for instance Kuosmanen (2012).
[7] For a more detailed review of this topic in SFA and DEA, see Johnson and Kuosmanen (2011, 2012).
[8] This method has been adopted by the Finnish regulator since 2012.

semi-parametric approximation to the random parameters model" (Greene, 2005b, p.299). The application of the LCM in efficiency analysis was first proposed by Orea and Kumbhakar (2004) and Greene (2005b).

The third approach included in Figure 1 involves several parametric models where the contextual variables are treated as inefficiency determinants.[9] They can be divided in three groups depending on how the *z*-variables are introduced in the model. As the inefficiency term in these models is defined as the truncation (over zero) of a normal distributed random variable, the contextual variables can be introduced in the model either through the pre-truncation mean as in Kumbhakar *et al.* (1991) and Battese and Coelli (1995), the pre-truncation variance as in Reifschneider and Stevenson (1991) or Caudill and Ford (1993), or simultaneously through the pre-truncation mean and variance, as in Alvarez *et al.* (2006) or Lai and Huang (2010). As this is the approach used in our paper, more details about these models can be found in the next section.

3. Theoretical model and empirical specification

In this section we introduce the theoretical cost model that allows us to analyse the economic characteristics of the technology, such as economies of scale or economies of density, of US electricity transmission firms. In general terms, the cost function to be estimated can be written as:

$$\ln C = \ln C\left(y, n, p, d, t\right) \tag{1}$$

where C is a measure of total costs, y is a vector of outputs, n measures the network length, p stands for input prices, d is a set of regional dummies and t represents the time trend. As usual, if firms minimize cost, this function should be linearly homogeneous with respect to input prices, and increasing in outputs.[10]

Economies of scale (*ES*) and density of electricity transmission firms can be computed once equation (1) is estimated. We associate economies of scale with *horizontal* system expansion, that is, increases in demand that require enlarging the current network to meet extra demand.[11] These economies can be then measured by the sum of cost elasticities with respect to the outputs, y, and the network length, n:

$$ES = \frac{\partial \ln C}{\partial \ln y} + \frac{\partial \ln C}{\partial \ln n} \tag{2}$$

On the other hand, we associate economies of density (*ED*) with *vertical* system expansion, i.e. expansion in transmitted electricity that do not require additional network. These economies can be measured by the sum of elasticity of cost with respect to the outputs, y:

[9] An interesting issue here is whether environmental variables should be included in the frontier (see later on the discussion in Section 4).

[10] Our cost variable is total expenditure (i.e. operating plus capital costs) due to the presence of possible trade-offs between operating and capital expenditures (Giannakis *et al.*, 2005). Regarding the set of output variables, we include the peak demand, transmission capacity and the energy delivered as cost drivers in electricity transmission (see Ofgem 2011, p.44-46).

[11] Note that here density is held constant because both output levels and network size is expanded simultaneously.

$$ED = \frac{\partial \ln C}{\partial \ln y} \tag{3}$$

In this case, the cost elasticity of network is not taken into account, as we are considering an increase in output levels, given the actual length of the transmission network.

We next allow for deviations with respect to the above cost function. The stochastic frontier literature suggests that these deviations should not be entirely attributed to uncontrollable or unobservable factors (i.e. random noise) but also to (managerial) inefficiency. To capture both sources of deviations, Aigner, Lovell and Schmidt (1977) proposed using an econometric specification of the cost function (1) that includes two random terms. This model (ALS henceforth) can be presented as follows:

$$\ln C_{it} = \alpha + X_{it}'\beta + v_{it} + u_{it} \tag{4}$$

where i stands for firms, t for time, X_{it} is a vector of explanatory variables, α and β are parameters to be estimated, $v_{it} \sim N(0,\sigma_v^2)$ is classical symmetric random noise, and u_{it} is a one-side error term which captures firms' inefficiency.

ALS assumed that this term follows a homoscedastic half-normal distribution, i.e. $u_{it} \sim N^+(0,\sigma_u^2)$. As the inefficiency term in ALS has constant variance, it does not allow the study of the determinants of firms' performance, which is the main issue examined in this paper. It might also yield biased estimates of both frontier coefficients and firm-specific inefficiency scores (see Caudill and Ford, 1993). To address this issue, we propose estimating a heteroscedastic frontier model that allows z-variables to be incorporated in the model as efficiency determinants. There are several options to achieve this using a parametric approach (see Figure 1) and the specific assumptions considered in these models might condition our results.[12] We follow referees' advice and explore alternative specifications of the model and carry out several model selection tests to choose the "best" model. In that sense Coelli *et al.* (2005) suggest exploring alternative models to assess the adequacy and robustness of the results obtained when a parametric approach is applied.

The most general specification of u_{it} that we consider in our paper is the general exponential model (GEM hereafter) introduced by Alvarez *et al.* (2006) that can be written as:[13]

[12] Similar problems might emerge when non- or semi-parametric approaches are used instead of a parametric approach. For instance, Martins-Filho and Yao (2013) point out that although the nonparametric approach considered by Kumbhakar *et al.* (2007) for estimating stochastic frontiers is quite general, the problem known as the curse of dimensionality could occur when the number of explanatory variables is large. This implies that one cannot be confident about the accuracy of the asymptotic approximation and the reliability of the efficiency estimates. Another example is the semi-parametric method known as StoNED presented by Kuosmanen (2012). This model allows introducing environmental variables in the model, but they can be interpreted either as factors that explain the inefficiency, or alternatively, as heterogeneity. Therefore this approach does not address whether environmental variables have a direct or indirect effect on the dependent variable. We discuss this issue in Section 4.

[13] Here we have adopted the notation used by Alvarez *et al.* (2006) and Lai and Huang (2010). Moreover, following Alvarez *et al.* (2006), we will use hereinafter the exponential functional form for the functions that incorporate environmental variables in all the estimated models. We found convergence problems and failed to get parameter estimates when we tried to estimate the models introduced by Battese and

$$u_{it} \sim N^{+}\left(\mu_{it}, \sigma_{uit}^{2}\right) \tag{5}$$

where

$$\mu_{it} = \exp\left(\delta_0 + z_{it}'\delta\right)$$

$$\sigma_{uit} = \exp\left(\gamma_0 + z_{it}'\gamma\right)$$

and δ_0, δ, γ_0 and γ are parameters to be estimated, and z_{it} is a vector of efficiency determinants. The two intercepts δ_0 and γ_0 in (5) allow us to get the homoscedastic frontier models. The environmental variables enter into this model both through the pre-truncation mean and variance of the inefficiency term, and hence the model allows for non-monotonic effects of the z-variables on firms' inefficiency (see Wang and Schmidt, 2002). Despite being a more comprehensive model than those usually presented in SFA, it is rarely estimated in the literature. For robustness grounds, we will also estimate more restricted models that are nested in the GEM and then some model selection tests will be performed for choosing the preferred specification.

The second estimated model has been proposed by Kumbhakar, Ghosh and McGuckin (1991), Huang and Liu (1994) and Battese and Coelli (1995) (hereafter KGMHLBC model). All of these authors consider a specification in which only the mean of the pre-truncated normal variable depends on environmental variables. In other words, it is assumed in this model that $\gamma=0$ in (5) and thus the variance of the pre-truncated normal variable is homoscedastic, i.e. $u_{it} \sim N^{+}(exp(\delta_0+z_{it}'\delta),\sigma_u^{2})$, where for notational simplicity we have relabelled $exp(\gamma_0)$ as σ_u.

The last two models are similar to the one estimated by Reifschneider and Stevenson (1991), Caudill and Ford (1993) and Caudill, Ford and Gropper (1995) (henceforth RSCFG models). In these papers the environmental variables are treated as determinants of the variance of the pre-truncated normal variable. In other words, they assume that $\delta=0$ in (5) and thus $u_{it} \sim N^{+}(\mu,(exp(\gamma_0+z_{it}'\gamma))^{2})$, where for notational ease $exp(\delta_0)$ has been relabelled as μ. If μ is allowed to be different from zero, we get the RSCFG-μ model introduced by Alvarez *et al.* (2006). This model nests the original RSCFG model in which μ=0 is imposed (i.e. $\delta_0=-\infty$ is assumed) and therefore it assumes that u_{it} follows a half-normal distribution, i.e. $u_{it} \sim N^{+}(0,(exp(\gamma_0+z_{it}'\gamma))^{2})$. As a consequence of this assumption, the so-called *scaling property* is satisfied in this model in the sense that the inefficiency term can be written as a deterministic function of a set of efficiency covariates, i.e. $h(\cdot)=\exp(z_{it}'\gamma)$, times a one-sided random variable that does not depend on any efficiency determinant, $u_{it}^{*} \sim N^{+}(0,\sigma_u^{2})$.

The defining feature of models with the scaling property is that firms differ in their mean efficiencies, but not in the shape of the distribution of inefficiency. That is, the scaling property implies that changes in z_{it} affect the scale but not the shape of u_{it}. In this model u_{it}^{*} can be viewed as a measure of "basic" or "raw" inefficiency that does not depend on any observable determinant of firms' inefficiency. On the other hand, the scaling function $h(\cdot)$ can be interpreted as the portion of total estimated inefficiency that

Coelli (1995) and Wang (2002) that use linear specifications of the pre-truncation mean. Lack of convergence is a frequent outcome when estimating SFA models due to the likelihood function being highly non-linear. Without opening a methodological discussion here, we feel that the lack of convergence in these models could be caused by the fact that μ_{it} is likely to be negative for some observations. In these cases, the distribution of u_{it} tends to be more symmetric, and this does not help to identify a one-sided error term. We thank Peter Schmidt for his well-founded comments on this issue.

researchers are able to explain with the variables included in *h(·)*. This function hence "adjusts" the underlying, and unexplained, inefficiency level upwards or downwards due to the influence of some potential inefficiency determinants. Although it has some features that make it attractive to some authors (see Wang and Schmidt, 2002), it is an empirical question whether or not the scaling property should be imposed, and not all commonly used models fulfil this property.[14]

To fully justify the choice of our preferred specification we will use the standard Likelihood Ratio (LR) test when comparing nested models (i.e. GEM vs. RSCFG-μ, GEM vs. KGMHLBC, RSCFG-μ vs. RSCFG, and RSCFG vs. ALS) and the Vuong (1989) test when they are non-nested (i.e. RSCFG-μ vs. KGMHLBC). It should be mentioned here that, although the standard RSCFG model is nested in the GEM model, they cannot be directly compared using standard LR tests because the GEM coefficients of the pre-truncation mean (i.e. δ) are not identified when μ=0 (as assumed in the RSCFG model). For the same reason, the ALS model cannot be compared against the KGMHLBC model using standard tests (i.e. δ is again not identified when μ=0). To test if μ=0, Alvarez *et al.* (2006) suggest carrying out a simple LR test using the RSCFG and RSCFG-μ models.

4. Data and sample

We use a panel data set of 59 US electricity transmission companies for the period 2001-2009. Most of these data were collected by various members of the EPRG (Energy Policy Research Group) at the University of Cambridge. That information was requested by Ofgem, in order to carry out an international benchmarking of electric utilities. Where the transmission operations are part of a larger utility - also involved in generation or distribution - shared costs are allocated on pro-rata basis. As can be seen in the data Appendix an allocation key - based on the ratio between wages and salaries specific from transmission and the total labour expenses of the utility - was used for the assignment of shared costs to transmission. The main source of the electricity transmission data was the FERC Form 1, an annual report of major electric utilities. The variables collected included the quantity of assets, voltage levels by asset, maximum demand, load density, demand growth, maturity of service area, age/condition of network, network density and flow patterns.[15]

Although the choice of input and output variables is an important issue, there is no clear consensus about the variables that should be included to describe the

[14] Another model that also satisfies this property is the so-called *scaled Stevenson* (SS) model introduced by Alvarez *et al.* (2006). In this model, both the mean and the variance of the pre-truncated normal depend on the environmental variables but the coefficients of the environmental variables in the pre-truncation mean and variance of *u* in (5) are the same, i.e. δ=γ. We will not provide the parameter estimates of this model in Section 5 because it collapsed to the KGMHLBC.

[15] The original dataset includes information of electricity and gas utilities in the US from 1994 to 2009 and also contains information on non-US firms from other countries for a shorter period. Following Ofgem's (2011, p.20) report, non-US transmission firms were not included in the analysis due to data limitations. Despite the initial proposal to undertake international benchmarking in that report, so far, these data have not been used. In our paper the sample was reduced to the last 9 years because labour costs in the electric power transmission industry are only available from 2001 to 2009. We have removed observations with missing and implausible values. We have also dropped a few isolated observations and maintained firms with (at least three) consecutive observations in order to minimize changes in our estimates when we change the specification of our model. It should be noted that this procedure does not give us a balanced panel, as we do not have the same number of observations per firm. Our final sample is an unbalanced panel data set of 402 observations without discontinuities across time.

performance of transmission and distribution companies. Jamasb and Pollitt (2001) show the wide range of variables that have been used in benchmarking analysis of electric utilities. They find that the most commonly used inputs in studies of electric utilities are operating costs, number of employees, transformer capacity, and network length. Regarding the outputs, the most included variables are units of energy delivered, number of customers, and the size of service area.

As we have mentioned in Section 3, our cost variable is Totex. This variable is the sum of Opex, which includes operation and maintenance expenses incurred by the company over one year, and Capex, which is the sum of annual depreciation on capital assets and the annual return on the balance of capital. Both Opex and Capex (and hence also Totex) are measured in year 2000 US dollars.[16]

Following the basic economic theory of production and the literature on electricity networks, we use as explanatory variables of total cost: three types of outputs, a variable that measures the system size, labour and capital price, a set of regional dummies and a time trend. Our output variables are: *Peak Load* (PL), *Electricity Delivered* (DE) and *Total Capacity of Substations* (CS). The first one is the maximum peak load of the year during 60 minutes and it might reflect transmission investment requirements given a fixed transmission capacity. The second one is the total annual energy delivered by the system which may imply an incremental effect in operating cost due to a greater use of electricity transmission assets. Due to a large amount of missing values in the data about voltage levels, we have introduced the CS as a proxy for the transmission capacity of the system. It is calculated as the sum of the total capacity of all substations in the transmission network.

In Figure 2 we show the evolution over time of the output variables divided by Totex, which can be interpreted as partial and observable productivity (efficiency) measures.[17] We can see in this figure a clear negative trend of the peak loads and the total capacity of substations given the total expenditure of each firm. In the case of electricity delivered, the temporal pattern of this variable is not so clear. These graphs give us a first idea about the negative evolution of the efficiency in our sample as the output level per dollar of cost, decreases, or in other words, the total unit cost per output, increases over time.

[Insert Figure 2]

Network length (NL) is usually viewed as one of the most important cost drivers of an electricity network (Jamasb and Pollitt, 2001). To measure the network length we have used pole miles. This variable measures the total sum of all transmission lines in miles regardless of the number of power cables on each power line. It is essentially a measure of the geographic spread of each company. We thought about using circuit miles instead pole miles, but the problem of circuit miles is that this variable refers to the number of power cables on each line multiplied by the distance between two points. Therefore it does not take into account the capacity of the cable so it is an unreliable measure of the physical infrastructure.

[16] RTO costs are included in the total costs. For more information about the calculation of Totex and the rest of variables, see the Appendix.

[17] As we have an unbalanced panel of 59 firms, to depict this figure we have selected those firms that are observed during the whole sample period, i.e. 28 firms. This avoids comparing different sets of firms in different periods.

Regarding input prices, we include in the cost function a *Labour Price* variable (LPR) defined as the average annual wage for the electric power transmission and distribution industry by state. As in the case of Totex, this variable is also measured in 2000 US dollars.[18] Regarding the *Capital Price* variable (KPR), we have used a producer price index for power transmission as a proxy for capital price. The source of these two variables is the Quarterly Census of Employment and Wages from the Bureau of Labor Statistics.

Taking into account the importance of controlling for differences in business environment from the perspective of corporate structures after US market liberalization, we have also included seven regional dummies that represent the regional reliability councils of the NERC in which the transmission utilities of our sample are located: *SERC Reliability Corporation* (SERC), *Southwest Power Pool* (SPP), *Western Electricity Coordinating Council* (WECC), *Northeast Power Coordinating Council* (NPCC), *ReliabilityFirst Corporation* (RFC), *Midwest Reliability Organization* (MRO) and *Electric Reliability Council of Texas* (ERCOT). We expect that these regional dummy variables are capturing (jointly with the other variables included in the model) most of the unobserved differences in the transmission companies' tasks, around the transportation of electricity, scheduling and dispatching of the plants, investment and maintenance of transmission assets, etc.[19]

Regardless of the introduction of these variables, we believe that there are three issues that should be mentioned related to the business environment as they might make a difference to transmission system efficiency in theory. The first is the presence or absence of incentive regulation in transmission. We have not included information about incentive regulation in our cost function because we do not have data on it. This is partly because each state is different and indeed each firm may have a different arrangement with its regulator. Identifying the arrangement for the transmission business as separate from the distribution business would be hard and a time series of the regimes would be needed for analysing this point. However we believe this issue should not affect the soundness of our results as it is not altogether clear what difference these things might actually make. Furthermore a detailed investigation of incentive regulation on efficiency is clearly out of the scope of this paper.

The second issue is the introduction of nodal pricing into the RTO, which might sharpen the pressure on transmission businesses to make lines available. However we have estimated a model including dummy variables that reflect the belonging to a certain RTO and this model is rejected in favour of our preferred model, which incorporates regional dummies for the NERC regions. Therefore our estimates suggest that once heterogeneity is controlled for, belonging to a certain RTO has a negligible impact on firms' efficiency. This may be because transmission systems have 99%+ availability, and hence the introduction of nodal prices may not have affected firms' performance. Furthermore RTOs do not 'regulate' total transmission revenue, so it is

[18] Unfortunately this information is not available at firm-level. Although it would be preferable to use firm-specific prices instead of state-level prices, as firm-level price data are not available in our application for both labour and capital, we have used the information that we found from statistical agencies. Clearly input prices do vary significantly across the US and it would be wrong not to adjust for them. In addition, we do not think there is much of a multi-state issue as the interesting thing is that transmission lines in the US are in fact mainly within one state.

[19] Another option to deal with this issue is using a model with fixed effects (see Greene, 2005a, 2005b, and more recently Wang and Ho, 2010). However, this estimation strategy does not easily deal with rarely changing variables, i.e. variables with little within or temporal variation such as network length or energy delivered. For a discussion on this issue, see Greene *et al.* (2011).

not clear why RTO membership should affect cost efficiency. This is because often it is the overall revenue of a transmission business that is regulated and poor revenue performance due to low availability on one line may lead to increased charges elsewhere.

Lastly, the third issue is the degree of vertical integration. Vertical integration might be independently significant, simply because of cost allocation issues and fixed costs being spread. Our preferred model does not contain any vertical integration variables (in particular backward integration into generation and the forward integration into distribution), because they were only significant for the 3% of the observations in our sample.[20]

Regarding the stochastic part of our cost function, we use 9 variables that are expected to affect firms' performance and, hence, they are included as efficiency determinants. In particular, we include the following variables: another time trend, three weather variables (minimum temperature, wind and precipitation), the Capex/Opex ratio and two variables that measure the growth of the demand.

Our weather variables have been obtained from the surface daily weather information collected by the National Climatic Data Center for the 2001-2009 period. The files are available for around 3,000 weather stations located in the US and contain information about: mean, maximum and minimum temperatures, precipitation amount, wind speed, number of days with snow, hail, tornadoes, etc. Given the high correlation among several weather variables, we decided to include one variable for each one of these categories: *Temperature* (TMIN), *Precipitation* (PRCP) and *Wind* (WIND). The temperature variable is the annual minimum temperature in Fahrenheit degrees, wind speed is the average of the daily mean wind speeds in knots, and precipitation is the average of the daily precipitation in inches. These weather variables are measured at the state-level, not at the firm-level. In order to obtain a unique value of each variable per state and year, we have taken the average among the weather stations within a particular state except for the case of the temperature variable which is the minimum value measured by any of the above stations along the year. Then, each utility was associated with the weather of the state where its principal office is located.[21] We hereafter assume that more adverse conditions appear when wind speed and precipitation are high and minimum temperature is low. These weather variables have also been introduced in the cost function as determinants of the technology, i.e. of the frontier cost function, in some of our estimated models.

As utilities may adapt their operating and investment practices over time to prevent power interruptions and to reduce the effect of adverse weather conditions, we interact our weather variables with the mean of the ratio of Capex and Opex (COR) for each firm i over the T_i available observations. We expect a negative coefficient if investing in Capex is an effective strategy in dealing with adverse weather conditions.

Finally we have included two variables that measure the average *Growth in Demand* for each firm over time. We distinguish between positive growth (POSGR) and negative growth (NEGR). The coefficients of these two variables should not be statistically significant if there are no adjustment costs and all inputs can be adjusted (without cost) from one year to the next. However, as the electricity industry is highly

[20] To examine this issue we have applied a modified version of the 'zero inefficiency stochastic frontier model' recently introduced by Kumbhakar *et al.* (2013).

[21] We recognise that this is a limitation especially when transmission companies may cover more than one state.

capital intensive with much of the assets becoming sunk cost upon investment, we expect significant coefficients for POSGR and NEGR. In particular, we expect a positive effect of POSGR on inefficiency indicating that utilities tend to anticipate future increases in their demand by investing in capital that is expected to be efficiently used in the future, but not in the present.[22] We expect a negative coefficient for NEGR if there is a negative trend in demand and reducing quasi-fixed input levels is expensive due to the existence of adjustment costs.

The descriptive statistics of all monetary, physical and environmental variables used in the stochastic cost frontiers are shown in Table 1.

[Insert Table 1]

5. Empirical results

We estimate a translog cost function that can be interpreted as a second-order approximation to the companies' underlying cost function.[23] All the variables included in the model are in logarithms, except the regional dummies and the time trend. Each explanatory variable is measured in deviations with respect to its mean, so the first-order coefficients can be interpreted as the cost elasticities evaluated at the sample mean. As usual homogeneity of degree one in prices is imposed, in this case by normalizing cost and labour price with capital price. Thus, the estimated equation can be written as follows:

$$\ln\left(\frac{C_{it}}{KPR_{it}}\right) = \alpha + \sum_{p=1}^{4} \beta_p \ln y_{pit} + \frac{1}{2}\sum_{p=1}^{4}\sum_{q=1}^{4} \beta_{pq} \ln y_{pit} \ln y_{qit} + \beta_L \ln\left(\frac{LPR_{it}}{KPR_{it}}\right) + \frac{1}{2}\beta_{LL}\left[\ln\left(\frac{LPR_{it}}{KPR_{it}}\right)\right]^2 + \sum_{p=1}^{4} \beta_{pL} \ln y_{pit} \ln\left(\frac{LPR_{it}}{KPR_{it}}\right) + \sum_{d=1}^{7} \beta_d NERC_d + \beta_t t + u_{it} + v_{it} \quad (6)$$

where for notational ease, the vector y stands for outputs and network length, i.e. y=(PL, DE, CS and NL).

As our results about firms' efficiency might depend on the empirical strategy followed to allow for inefficiency determinants, we first carry out several model selection tests to select the best specification supported by the data. Table 2 shows the LR tests for nested models, where the second model presented in each line is nested in the first model. Firstly we can see that the ALS model is rejected in favour of the RSCFG model due to the inclusion of environmental variables in the variance of the heteroscedastic inefficiency term. This latter model is in turn rejected in favour of the RSCFG-μ, indicating that the inefficiency term does not follow a half normal distribution. Table 2 also displays the Vuong test for the non-nested RSCFG-μ and KGMHLBC models. A positive value indicates that the first model is preferred to the

[22] As Jamasb and Pollitt (2007) and Poudineh and Jamasb (2015) note, achieving long-term efficiency improvements can involve short-term increases in Capex or Opex that may not generate immediate efficiency improvements. In fact, increases in short-term expenditure can deteriorate the firms' short-term relative performance. This might in turn discourage firms from efficiency-improving investments that have long-term gains.

[23] The more restricted Cobb-Douglas specification was always rejected in favour of the translog specification.

second one. In this case we can see that the preferred model is the RSCFG-μ model. Lastly, the LR tests in Table 2 again indicate that GEM clearly outperforms both RSCFG-μ and KGMHLBC models. Based on these comparisons, we will use the GEM model to examine in detail the estimated levels of cost efficiency.

[Insert Table 2]

Moreover it can be debated whether the exponential specification of the pre-truncation mean in the presented models could be an unnecessary restriction in our application as it imposes positive values for μ.[24] In order to examine this issue, we have also estimated a *linear* RSCFG-μ model (not shown here) that does not use an exponential specification of μ, so now the estimated μ could be either positive or negative. The estimated μ was positive and statistically different from zero. Moreover, the estimated value (0.86) coincides with the exponent of the estimated intercept (-0.16) in our exponential specification of the RSCFG-μ model. Therefore, this result suggests that restricting μ to be positive is likely not to be a binding restriction in our application.

In addition to the frontier parameters that are discussed later on, Table 3 displays the coefficients of the inefficiency term that have been estimated using the standard homoscedastic ALS model, and the heteroscedastic models presented before: RSCFG, RSCFG-μ, KGMHLBC and GEM. Although the environmental variables in the GEM model are included both in the pre-truncation mean and the variance of the inefficiency term, their main effect is through the variance. Indeed, whereas most of the coefficients of the variables included as determinants of the variance of the inefficiency term are statistically significant, the estimated coefficients for the pre-truncation mean are not significant (except for the time trend which is negative and significant at a 90% confidence level). This is in line with our finding that the coefficients of these variables in the RSCFG and RSCFG-μ models are also significant, but not in the KGMHLBC model. The latter model clearly shows that the mean of the inefficiency is not able to capture the effect of the environmental variables on firms' inefficiency. Thus, we will focus our comments on the variance of the inefficiency term.

[Insert Table 3]

Regarding the inefficiency variance, our results indicate that weather is an important issue in this industry.[25] Wind speed and precipitation have a positive and significant coefficient indicating that more adverse conditions generate higher levels of inefficiency. The negative sign for the minimum temperature also suggests (although it is not significant) that a lower minimum temperature slightly increases cost due to higher levels of firms' inefficiency.

Overall, the above discussion suggests the existence of a significant effect of weather conditions on firms' inefficiency. Our results thus seem to indicate that unfavourable weather conditions are a real hurdle in managing electricity transmission firms. As the environment is not controlled by the firms, they should not be blamed for their environment-induced inefficiency. This implies that regulators should purge the data when environmental conditions are part of the technology and/or have an indirect effect through inefficiency.

The introduction of the average ratio of Capex and Opex (COR) interacting with the weather variables allows us to catch an idea about the best strategy for the

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[24] We thanks one of the referees for pointing out this issue.
[25] Note also that the coefficient of the time trend is positive, showing that the effect of time is different in both parts of the inefficiency.

companies to deal with adverse weather conditions. The estimated coefficients have the opposite sign to those obtained for the isolated weather variables, indicating that, as expected, more capital-intensive utilities (e.g. with higher capital-to-opex ratios) are able to better mitigate the effect of unfavourable weather conditions. They are, *ceteris paribus*, more efficient than those utilities using a higher proportion of operating inputs. This result suggests therefore that investing in equipment is an effective strategy in mitigating the effects of unfavourable weather conditions.

The last set of efficiency determinants has to do with growth in demand. We obtain a positive, and significant, coefficient for POSGR, indicating that utilities are more efficient when the demand is constant as they do not need to anticipate investments to meet future demand. However, the coefficient of NEGR is not significant in most of the models, indicating perhaps that reducing quasi-fixed inputs is not expensive for the companies or that maintaining the underused network is not very costly when there is a negative trend in the demand growth.

In Figure 3 we depict the histogram of estimated levels of cost efficiency. The average efficiency in our sample is 88% using our preferred model. Pollitt (1995) using 1990 data found an average efficiency of 80% for the total of the companies in his sample and 88.3% for larger firms. The latter value is very similar to the one that we have found with our preferred model. This seems to indicate that the relative performance of the electricity transmission utilities has not experienced a significant improvement from one period to the next.

[Insert Figure 3]

We show in Figure 4 the temporal evolution of our efficiency scores using the GEM model.[26] The graph shows that the average efficiency score decreases over time, starting at 93.9% and finishing at 82.2%. Consequently, the negative sign of the coefficient for the time trend through the pre-truncation mean of u in our model seems not to offset its positive value through the variance. Our preferred model also indicates an increasing divergence in firms' performance over time. Overall, the estimated evolution in performance and the lack of convergence in firms' inefficiency scores seem to suggest that there is scope for improvements in the performance of the US electricity transmission system.

[Insert Figure 4]

We next focus our discussion on the estimated frontier parameters, also shown in Table 3. In general, all models perform quite well as most of the first-order coefficients have the expected sign and their magnitudes are quite reasonable from a theoretical point of view. Certainly, the coefficients of the three outputs and network length are always positive and mostly statistically different from zero when measuring the incremental costs associated with either higher maintenance and operational costs or the need for new capital. A similar statement can be made about the coefficients on input prices, which are also positive and statistically significant. The coefficients on many of the dummy variables for the NERC regions are also significant indicating that, regardless of the rest of firms' features, regional differences exist. The coefficient on the

[26] Except for the RSCFG and the RSCFG-μ models, which exhibit a similar evolution of the efficiency (not shown), the rest of the estimated models present clear differences with respect to the GEM, our preferred model. These differences might be taken as an anecdotal evidence of the biases that might appear in an empirical application when inefficiency determinants are not taken into account or are misplaced in the specification of the model.

time trend is negative (nonetheless it is not significant in some of the models), which indicates that costs decrease over time, i.e. there is positive technical change.

As the selection of the output set is often quite contentious, we have carried out several LR tests to fully justify the explanatory variables that were included in our cost frontier function. Table 4 shows several tests where our specification of the GEM model is compared to more restricted specifications where one of the outputs is excluded from the output set. As can be seen, all the output variables that were introduced in the model, and primarily peak load (PL) and network length (NL), are relevant cost drivers and should be taken into account in any analysis. We also test - in this table - for the inclusion of dummy variables that reflect the belonging to a certain RTO or alternatively to a certain NERC region. In both cases the LR test values indicate that the model that is rejected is the one that does not include any regional dummy.[27]

[Insert Table 4]

Next, we use our preferred model, GEM, to examine some characteristics of the estimated technology. As in previous papers, the estimated elasticities allow us to measure economies of scale and density, but in this case using more recent data. Figure 5 depicts the elasticity of total cost with respect to peak load, delivered electricity, total capacity of substations and network length estimated for each observation, sorted in increasing order. Peak load seems to be the most important cost driver with an average elasticity equal to 0.54. This figure also allows us to examine the reliability of our estimated elasticities when we move away from the sample mean. The first derivative of our cost function provides a first-order approximation to the underlying elasticity at the sample mean. However, most observation-specific elasticities have a reasonable order of magnitude, except for the negative values on the left in three of the curves. In these cases, our estimates should be viewed with caution as they correspond to some observations which are far away from the sample mean.[28]

[Insert Figure 5]

Adding the first-order coefficients of the three outputs we find that the elasticity of density evaluated at the sample mean is quite similar in all models, varying from 0.70 to 0.75. These values suggest the existence of important economies of density in the electricity transmission industry. That is, given network infrastructure, electricity transmission networks exhibit natural monopoly characteristics.

To analyse the economies of scale, which involve expansions in both output and network, we need to add the cost elasticity of the network length to the elasticity of density. The elasticity of scale evaluated at the sample mean in the GEM model is 0.89. Figure 6 compares both elasticities. More than half of the firms in our sample exhibit increasing returns to scale. These results suggest that electricity transmission networks

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[27] Moreover, a Vuong test not shown in Table 4 indicates that the model which includes RTO dummies is rejected in favour of our preferred model, which incorporates regional dummies for the NERC regions.

[28] For most functional forms (e.g. the translog function) there is a fundamental trade-off between flexibility and theoretical consistency. For instance, maintaining global monotonicity (e.g. positive elasticities and marginal costs) is impossible without losing second order flexibility. Barnett *et al.* (1996) show that the monotonicity requirement is by no means automatically satisfied for most functional forms, and that violations are frequent. However to show the robustness of our estimates we have tested the monotonicity conditions using the well-known Wald test. We only find statistically negative values for 0.25% of the observations in the case of electricity delivered, 4.98% for the network length and zero for the other outputs. The small number of negative elasticities found gives us confidence about the fulfilment of the monotonicity conditions on outputs and hence about the suitable properties of the estimated cost function.

still exhibit natural monopoly characteristics when a network is expanded to meet the extra demand. Using data for 1990, Pollitt (1995) finds different degrees of economies of scale depending on firms' size for the US transmission utilities. In particular, he finds that decreasing returns to scale are more common in small utilities while increasing returns to scale are more common in medium and large companies. This seems to be consistent with the results obtained here, as in our sample we mainly have large firms. Dismukes *et al.* (1998) also show that all the NERC reliability regions in the US exhibit significant economies of scale for the transmission companies, while Huettner and Landon (1978) find that of six expenses categories, only sales expenses exhibits increasing returns to scale over the whole of the observed output range.

[Insert Figure 6]

Next we focus our discussion on weather issues. Our models only include the weather variables as inefficiency determinants because we have not been able to find a direct cost effect associated with different weather conditions.[29] This does not preclude however a significant direct effect for some observations. An observation-by-observation analysis of this issue can be carried out if we estimate our models using a LCM structure.[30] In particular, we propose estimating a modified version of the so-called zero inefficiency stochastic frontier model introduced by Kumbhakar *et al.* (2013) to examine differences in performance (i.e. inefficiency). Here we have adapted this framework to capture the differences in technology. Our LCM allows estimating two different cost frontiers: with and without weather variables. As in the zero-inefficiency model, the other parameters of our model are assumed to be the same in both groups (classes).[31] If most firms belong to the class with no weather variables as determinants of the cost frontier, we then can conclude that our original cost frontier is already capturing their direct effect on firms' costs. The assigning of the firms to a particular group is performed by the model using class-membership probabilities, without any prior assumption by the researcher about the classification of the firms.

Table 5 shows the proportion of observations that are located in either the group with or without weather variables as relevant cost frontier drivers. In both cases, we have used our preferred GEM model specification. It should be first pointed out that the discriminatory capacity of the LCM to allocate firms in different classes is quite robust as the posterior class probabilities are very large. The numbers in this table show that only 1% of the observations would be assigned to the class that includes weather variables in the frontier (class 2).[32] A similar percentage is also obtained when we add the interactions of the weather variables with the variable measuring firms' cost

[29] This result is conditional on our set of regional dummies.

[30] We have carried out additional model selection tests to choose the proper model specification in the LCM framework. The values of the performed Chi-squared tests (with 9 degrees of freedom) were 65.9 and 21.7 for the LCM specification of KGMHLBC and RSCFG-μ, respectively. These values allow us to reject the restrictions imposed by these two models, and therefore the LCM specification of the GEM model is again the preferred one.

[31] In particular, while the cost frontier of one group is simply $\ln C = \ln C(X, \beta)$, the cost frontier of the second group includes weather (i.e. z) variables and can be written as $\ln C = \ln C(X, \beta) + z'\psi$. Moreover, the frontier parameters associated to non-weather variables (β), and the parameters describing the distribution of v and $u(z)$ are imposed to be the same in both classes. Therefore, the issue here is to identify the set of firms with ψ=0 or not. As the value of ψ is not available to the econometrician, class membership probabilities should be estimated simultaneously alongside the other parameters of the model. See Orea and Kumbhakar (2004) for more details about these models.

[32] These five observations come from 4 different firms and all of them, except one, show large posterior probabilities (higher than 90%) of belonging to class 2.

structure. These results suggest that only the costs of a small number of firms could be "fully" adjusted downwards due to the direct negative influence of the bad weather.

[Insert Table 5]

The lack of a direct (or frontier) cost effect attributable to different weather conditions may appear somewhat counterintuitive. However, this result is to be expected if other explanatory variables, especially the regional dummy variables, are actually capturing the frontier effect of weather on firms' costs. We have checked this and have found (using a multinomial logit model) that our set of NERC regional dummies is jointly correlated with the set of weather variables. Moreover, some of the output variables (such as PL) and technological variables included in the cost frontier are also correlated with the weather variables. These correlation analyses indicate that any frontier effect of weather on firms' costs is already captured by the model, a result which indicates that the environmental factors are already taken into account in the design of networks, as pointed out by Jamasb *et al.* (2012). Therefore, it seems that advance planning has reduced the need to undertake corrective expenditure in response to outages caused by adverse weather conditions.

We have been able to take advantage of both the estimated GEM and multinomial logit models to provide some information on the direct effect of weather on firms' cost. The estimated coefficients of the multinomial logit model first allow us to compute for each firm/observation the probability of belonging to a particular NERC region, given the values of the weather variables. We then can predict the cost associated to the actual weather conditions if we multiply the computed probabilities (evaluated at the actual weather values) by the estimated coefficients of our regional dummies in the GEM model. We find a correlation of 70% between these values and those obtained by actually being located in a specific NERC region. This indicates that most of the cost effect of our regional dummies has to do with weather conditions.[33] We also find that the direct cost effect of being located in a region with bad (rather than good) weather conditions is on average about 8%.[34]

Finally, we provide information on the weather effect on firms' efficiency. For this purpose we consider the above hypothetical weather scenarios: good and bad. The efficiency score of a company operating under 'standard' weather conditions is 94%. The efficiency score would be 98% under good weather conditions, while the expected score under bad weather conditions would be 80%.[35] Therefore, the extra costs caused by this deterioration in firms' performance due to unfavourable weather conditions are about 19%. We have also found that the computed extra costs tend to be larger for those more inefficient companies, so they may deserve a more generous treatment when adjusting their costs.

In summary, from the empirical analysis performed in this paper we can make three suggestions for carrying out the benchmarking of electricity transmission utilities. First, the effect of weather conditions on firms' costs is a material issue that should not be overlooked by the regulator. For this reason, it would be advisable to adjust the cost data of the companies *prior to* undertaking a benchmarking. Some regulators, such as Ofgem in Great Britain, are at least partly doing this by excluding extreme weather

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[33] In addition, as this correlation is not 100%, this confirms that the regional dummies are capturing additional issues.

[34] The good and bad weather scenarios have been computed using the average weather conditions of those observations that are above or below the sample mean.

[35] These percentages have been computed using the Wang's (2002) formula for $E(u|z)$.

costs. Otherwise, capturing their effect during the benchmarking exercise is not an easy task.[36] Second, if the cost data have not been previously adjusted or this has not been properly done, we recommend the use of heteroscedastic SFA models that allow the inclusion of efficiency determinants.[37] If not, we could be both ignoring much of the weather effects on firms' costs and biasing our estimates of firms' efficiency. The use of heteroscedastic SFA models is more important in a regulatory framework where the incentives are significantly based on firms' relative performance. Finally, although the decision about the location of the environmental variables should be based on statistical grounds, we also recommend including these variables in the cost frontier in order to capture any direct effect on firms' costs that has not already been captured by other explanatory variables.

6. Conclusions

The electricity industry in most developed countries has been restructured in recent decades with the aim of reducing costs, improving service quality and encouraging electric utilities to perform efficiently. The remaining regulated segments (i.e. transmission and distribution) provide the infrastructure for the competitive segments and represent an important share of the total price paid by final customers. Despite the fact that electricity transmission is an essential part of the electricity supply sector there is a lack of empirical studies that analyse both economic characteristics of the technology and firms' performance in electricity transmission.

To fill this gap in the literature we have analysed firms' efficiency in the US electricity transmission industry for the period 2001-2009. The analysis of the economic characteristics of the technology and inefficiency of US utilities relies on the estimation of several stochastic cost frontiers. The estimated coefficients provide useful information about firm's performance with both policy and managerial implications. For instance, we have found that, given network infrastructure, electricity transmission networks exhibit natural monopoly characteristics in most cases. This result provides support for the continuing regulation of electricity transmission. Moreover, our results indicate that average efficiency in the US electricity transmission industry has declined (and diverged) over the period 2001-2009, suggesting that there is room for improvement in performance of the US electricity transmission system.

Our stochastic frontier models also allow us to identify the determinants of firms' inefficiency in this industry. In particular, as determinants of firms' inefficiency, we have included several variables capturing weather conditions, companies' cost structure, and energy demand growth. The results indicate that more adverse conditions generate higher levels of inefficiency and hence our findings confirm that it is indeed more difficult to manage a firm operating in a region with bad weather.

We have also found that investing in capital is an effective strategy to deal with adverse weather conditions to avoid incurring additional operating costs. This might suggest a regulatory framework that favours capital investments to deal with unfavourable weather conditions. Finally we have found that, as expected, firms' performance gets better when demand tends to be steady as firms cannot adjust their

[36] Indeed, the weather conditions might have a direct effect, an indirect effect, or both. We have found that it could be difficult to identify the direct effect due to collinearity problems. The effect through the inefficiency term is also a challenge, as it might have non-linear effects on firms' inefficiency.
[37] Obviously, this suggestion can be extended to a nonparametric context.

inputs without cost over time. This result, combined with the previous finding on the importance of capital expenditure to deal with weather conditions, suggests that regulators should acknowledge that achieving long-term efficiency improvements can involve short-term increases in both capital and operational costs and, hence, a deterioration in firms' short-term relative performance.

References

Aigner, D., Lovell, K. and Schmidt, P. (1977), “Formulation and estimation of stochastic frontier production function models”, *Journal of Econometrics*, 6, 21-37.

Alvarez, A., Amsler, C., Orea, L. and Schmidt, P. (2006), “Interpreting and testing the scaling property in models where inefficiency depends on firm characteristics”, *Journal of Productivity Analysis*, 25, 201-212.

Banker, R.D. and Morey, R. (1986), “Efficiency analysis for exogenously fixed inputs and outputs”, *Operations Research*, 34, 513-521.

Barnett W.A., Kirova, M., and Pasupathy, M. (1996), “Estimating policy invariant deep parameters in the financial sector, when risk and growth matter”, *Journal of Money Credit and Banking*, 27, 1402-1430.

Battese, G.E. and Coelli, T.J. (1995), “A model for technical efficiency for panel data”, *Empirical Economics*, 20, 325-332.

Billinton, R. and Acharya, J. (2005), “Consideration of multi-state weather models in reliability evaluation of transmission and distribution systems”, *Proceedings of the Canadian Conference on Electrical and Computer Engineering*, 619-622.

Billinton, R. and Wenyuan, L. (1991), “Novel method incorporating weather composite system adequacy evaluation”, *Transactions on Power Systems, IEEE*, 6(3), 1154-1160.

Billinton, R. and Wu, C. (2001), “Predictive reliability assessment of distribution system including extreme adverse weather”, *Canadian Conference on Electrical and Computer Engineering*, 2, 719-724.

Brown, R.E. (2002), *Electric power distribution reliability*, New York, Marcel Dekker.

Brunekreeft, G., Neuhoff, K. and Newbery, D. (2005), “Electricity transmission: An overview of the current debate”, *Utilities Policy*, 13(2), 73-93.

Caudill S.B, and Ford J.M. (1993), “Biases in frontier estimation due to heteroscedasticity”, *Economic Letters*, 41, 17-20.

Caudill, S.B., Ford, J.M. and Gropper, D.M. (1995), “Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity”, *Journal of Business and Economic Statistics*, 13, 105-11.

Coelli, T.J., Rao, D.S.P., O’Donnell, C.J. and Battese, G.E., (2005), *An introduction to efficiency and productivity analysis*, 2nd ed., Springer.

Dismukes, D.E., Cope III, R.F. and Mesyanzhinov, D. (1998), “Capacity and economies of scale in electric power transmission”, *Utilities Policy*, 7(3), 155-162.

Fried, H.O., Lovell, C.A.K., Schmidt, S.S. and Yaisawarng, S. (2002), “Accounting for environmental effects and statistical noise in data envelopment analysis”, *Journal of Productivity Analysis*, 17, 157-174.

Giannakis, D., Jamasb, T. and Pollitt, M. (2005), “Benchmarking and incentive regulation of quality of service: an application to the UK electricity distribution networks”, *Energy Policy*, 33(1), 2256-2271.

Greene, W. (2005a), "Fixed and random effects in stochastic frontier models", *Journal of Productivity Analysis*, 23, 7-32.

Greene, W. (2005b), "Reconsidering heterogeneity in panel data estimators of the stochastic frontier model", *Journal of Econometrics*, 126, 269-303.

Greene, W., Orea, L. and Wall, A. (2011), *A one-stage random effect counterpart of the fixed-effect vector decomposition model with an application to UK electricity distribution utilities*, Efficiency Series Papers 01/2011, Oviedo Efficiency Group, University of Oviedo.

Greenfield D. and Kwoka, J. (2011), "The cost structure of regional transmission organizations", *The Energy Journal*, 32(4), 159-181.

Growitsch, C., Jamasb, T. and Wetzel, H. (2012), "Efficiency effects of observed and unobserved heterogeneity: Evidence from Norwegian electricity distribution networks", *Energy Economics*, 34(2), 542-548.

Haney, A.B. and Pollitt, M. (2009), "Efficiency analysis of energy networks: An international survey of regulators", *Energy Policy*, 37, 5814-5830.

Haney, A.B. and Pollitt, M. (2013), "International benchmarking of electricity transmission by regulators: A contrast between theory and practice?", *Energy Policy*, 62, 267-281.

Huang, C.J. and Liu, J.T. (1994),"Estimation of non-neutral stochastic frontier production function", *Journal of Productivity Analysis*, 5(2), 171-180.

Huettner, D.A., and Landon, J.H. (1978), "Electric utilities: Scale economies and diseconomies", *Southern Economic Journal*, 44(4), 883-912.

Jamasb, T. and Pollitt, M. (2001), "Benchmarking and regulation: International electricity experience", *Utilities Policy*, 9(3), 107-130.

Jamasb, T. and Pollitt, M. (2005), "Electricity market reform in the European Union: Review of progress toward liberalization and integration", *The Energy Journal*, 26(special I), 11-41.

Jamasb, T. and Pollitt, M. (2007), "Incentive regulation of electricity distribution networks: Lessons of experience from Britain", *Energy Policy*, 35(12), 6163-6187.

Jamasb, T., Orea, L. and Pollitt, M. (2010), *Weather factors and performance of network utilities: A methodology and application to electricity distribution*, EPRG Working Paper 1020, Cambridge Working Paper in Economics 1042, University of Cambridge.

Jamasb, T., Orea, L. and Pollitt, M. (2012), "Estimating the marginal cost of quality improvements: The case of the UK electricity distribution companies", *Energy Economics*, 34(5), 1498-1506.

Joskow, P.L. (2014), "Incentive regulation in theory and practice: Electricity distribution and transmission networks", Chapter in NBER book *Economic regulation and its reform: What have we learned?*, Nancy L. Rose (ed.), 291-344, National Bureau of Economic Research, Inc.

Johnson, A.L. and Kuosmanen, T. (2011), "One-stage estimation of the effects of operational conditions and practices on productive performance: Asymptotically normal and efficient, root-n consistent StoNEZD method", *Journal of Productivity Analysis*, 36(2), 219-230.

Johnson, A.L. and Kuosmanen, T. (2012), "One-stage and two-stage DEA estimation of the effects of contextual variables", *European Journal of Operational Research*, 220(2), 559-570.

Kumbhakar, S.C., Ghosh, S. and McGuckin, J.T. (1991), "A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms", *Journal of Business and Economic Statistics*, 9, 279-286.

Kumbhakar, S.C., Park, B.U., Simar, L. and Tsionas, E.G. (2007), "Nonparametric stochastic frontiers: A local maximum likelihood approach", *Journal of Econometrics*, 137, 1-27.

Kumbhakar, S.C., Parmeter, C.F. and Tsionas, E.G. (2013), "A zero inefficiency stochastic frontier model", *Journal of Econometrics*, 172(1), 66-76.

Kuosmanen, T. (2012), "Stochastic semi-nonparametric frontier estimation of electricity distribution networks: Application of the StoNED method in the Finnish regulatory model", *Energy Economics*, 34, 2189-2199.

Lai, H. and Huang, C.J. (2010), "Likelihood ratio tests for model selection of stochastic frontier models", *Journal of Productivity Analysis*, 34, 3-13.

Li, Q., Huang, C., Li, D. and Fu, T. (2002), "Semiparametric smooth coefficient models", *Journal of Business and Economic Statistics*, 20(3), 412-422.

Martins-Filho, C. and Yao, F. (2013), "Semiparametric stochastic frontier estimation via profile likelihood", *Econometric Reviews*, 34(4), 413-451.

Llorca, M., Orea, L. and Pollitt, M.G. (2014), "Using the latent class approach to cluster firms in benchmarking: An application to the US electricity transmission industry", *Operations Research Perspectives*, 1(1), 6-17.

Muñiz, M.A. (2002), "Separating managerial inefficiency and external conditions in data envelopment analysis", *European Journal of Operational Research*, 143, 625-643.

Nillesen, P. and Pollitt, M. (2010), "Using regulatory benchmarking techniques to set company performance targets: The case of US electricity", *Competition and Regulation in Network Industries*, 11(1), 50-85.

Ofgem (2011), *Decision on strategy for the next transmission price control - RIIO-T1. Tools for cost assessment*, March 2011. Office of Gas and Electricity Markets, London.

Orea, L. and Kumbhakar, S. (2004), "Efficiency measurement using stochastic frontier latent class model", *Empirical Economics*, 29, 169-183.

Orea, L., Growitsch, C. and Jamasb, T. (2015), "Using supervised environmental composites in production and efficiency analyses: An application to Norwegian electricity networks", *Competition and Regulation in Network Industries*, 16(3), 260-288.

Pollitt, M. (1995), *Ownership and performance in electric utilities*, Oxford University Press, Oxford.

Poudineh, R. and Jamasb, T. (2015), “A new perspective: Investment and efficiency under incentive regulation”, *The Energy Journal*, 36(4), 241-263.

Ray, S.C. (1988), “Data envelopment analysis, nondiscretionary inputs and efficiency: An alternative interpretation”, *Socio-Economic Planning Sciences*, 22(4), 167-176.

Reifschneider D. and Stevenson R. (1991), “Systematic departures from the frontier: A framework for the analysis of firm inefficiency”, *International Economic Review*, 32, 715-723.

Rothstein, B. and Halbig, G. (2010), *Weather sensitivity of electricity supply and data services of the German Met Office*, Management of Weather and Climate Risk in the Energy Industry, A. Troccoli (ed.), 253-266.

Ruggiero, J. (1996), “On the measurement of technical efficiency in the public sector”, *European Journal of Operational Research*, 90, 553-565.

Simar, L. and Wilson, P.W. (2007), “Estimation and inference in two-stage, semi-parametric models of production processes”, *Journal of Econometrics*, 136(1), 31-64.

Stevenson, R.E. (1980), “Likelihood functions for generalized stochastic frontier estimation”, *Journal of Econometrics*, 13, 57-66.

Sun, K. and Kumbhakar, S.C. (2013), “Semiparametric smooth-coefficient stochastic frontier model”, *Economic Letters*, 120, 305-309.

von Geymueller, P. (2009), “Static versus dynamic DEA in electricity regulation: The case of US transmission system operators”, *Central European Journal of Operations Research*, 17, 397-413.

Vuong Q.H. (1989), “Likelihood ratio tests for model selection and non-nested hypotheses”, *Econometrica*, 57(2), 307-333.

Wang, H.J. and Ho, C.W. (2010), “Estimating fixed-effect panel stochastic frontier models by model transformation”, *Journal of Econometrics*, 157, 286-296.

Wang, H.J. (2002), “Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model”, *Journal of Productivity Analysis*, 18, 241-253.

Wang, H.J. and Schmidt, P. (2002), “One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels”, *Journal of Productivity Analysis*, 18, 129-144.

Yu, W., Jamasb, T. and Pollitt, M. (2009), “Does weather explain cost and quality performance? An analysis of UK electricity distribution companies”, *Energy Policy*, 37(11), 4177-4188.

Table 1.Descriptive statistics

	Variable	*Units*	*Mean*	*Max.*	*Min.*	*Std. Dev.*
Totex	Cost	US$	145,111,000	667,127,000	20,713,600	120,627,000
Peak Load	Output	MW	6,208	23,111	380	5,539
Electricity Delivered	Output	MWh	6,279,730	74,584,700	56,730	8,872,920
Total Capacity of Substations	Output	MVA	27,821	120,115	1,327	22,720
Network Length	Network	Miles	4,073	16,292	1,087	3,263
Annual Salary	Input Price	US$	62,144	94,005	34,024	10,531
Producer Price Index	Input Price	Index	179.21	222.40	155.00	21.35
SERC	Dummy	-	0.40	1	0	0.49
SPP	Dummy	-	0.22	1	0	0.41
WECC	Dummy	-	0.26	1	0	0.44
NPCC	Dummy	-	0.04	1	0	0.21
RFC	Dummy	-	0.25	1	0	0.43
MRO	Dummy	-	0.14	1	0	0.35
ERCOT	Dummy	-	0.04	1	0	0.21
Minimum Temperature	Weather	°F	-10.35	19.90	-59.80	16.57
Wind Speed	Weather	Knots	6.83	9.60	4.63	1.01
Precipitation	Weather	Inches	0.07	0.16	0.01	0.03
Capex/Opex	Other	Ratio	1.18	5.90	0.13	0.70
Growth in Demand	Other	%	0.03	244.11	-74.96	17.77

Table 2. Model selection tests

Comparison of nested models (LR test)	***Test value***	***D.o.f.***	***Preferred model***
RSCFG vs. ALS	74.052 ***	9	RSCFG
RSCFG-μ vs. RSCFG	37.137 ***	1	RSCFG-μ
GEM vs. RSCFG-μ	18.163 **	9	GEM
GEM vs. KGMHLBC	101.802 ***	9	GEM

Comparison of non-nested models (Vuong test)	***Test value***	***Preferred model***
RSCFG-μ vs. KGMHLBC	1.830 *	RSCFG-μ

Significance code: * p<0.1, ** p<0.05, *** p<0.01

Table 3. Parameter estimates of the translog cost function

		ALS			*RSCFG*			*RSCFG-μ*			*KGMHLBC*			*GEM*		
	Parameters	***Est.***		***Est./s.e.***	***Est.***		***Est./s.e.***	***Est.***		***Est./s.e.***	***Est.***		***Est./s.e.***	***Est.***		***Est./s.e.***
Frontier	Intercept	13.208	***	169.471	13.391	***	231.108	12.573	***	83.435	13.394	***	65.985	13.294	***	202.786
	$\ln PL_{it}$	0.508	***	8.148	0.523	***	11.160	0.452	***	11.161	0.616	***	11.249	0.545	***	12.233
	$\ln DE_{it}$	0.057	***	2.808	0.060	***	3.527	0.024	**	2.002	0.040	*	1.853	0.061	***	3.945
	$\ln CS_{it}$	0.138	**	2.034	0.164	***	2.896	0.349	***	6.917	0.056		0.884	0.140	**	2.517
	$\ln NL_{it}$	0.145	***	3.918	0.135	***	4.296	0.016		0.583	0.064	*	1.776	0.145	***	4.841
	$\ln (LPR_{it}/KPR_{it})$	0.582	***	3.722	0.528	***	4.399	0.448	***	4.398	0.422	**	2.502	0.497	***	4.113
	$½ (\ln PL_{it})^2$	-0.057		-0.288	-0.037		-0.223	-0.248	**	-1.999	0.271		1.308	0.044		0.292
	$½ (\ln DE_{it})^2$	0.038		1.415	0.040	**	2.198	0.032	**	2.021	0.017		0.639	0.044	**	2.338
	$½ (\ln CS_{it})^2$	0.167		0.526	0.109		0.422	0.077		0.372	0.304		0.825	0.119		0.536
	$½ (\ln NL_{it})^2$	0.270	**	2.077	0.247	***	2.962	0.380	***	6.213	0.196	*	1.677	0.253	***	3.278
	$½ (\ln (LPR_{it}/KPR_{it}))^2$	0.121		0.183	-0.139		-0.278	-0.319		-0.852	-0.159		-0.235	-0.012		-0.026
	$\ln PL_{it} \cdot \ln DE_{it}$	-0.005		-0.085	-0.032		-0.764	0.009		0.273	0.037		0.619	-0.021		-0.540
	$\ln PL_{it} \cdot \ln CS_{it}$	0.015		0.060	0.077		0.368	0.240		1.507	-0.346		-1.220	-0.002		-0.013
	$\ln PL_{it} \cdot \ln NL_{it}$	0.061		0.482	0.182	**	2.098	0.182	***	2.837	0.002		0.019	0.155	*	1.800
	$\ln PL_{it} \cdot \ln (LPR_{it}/KPR_{it})$	-0.152		-0.500	-0.085		-0.323	0.084		0.401	-0.277		-0.978	-0.160		-0.697
	$\ln DE_{it} \cdot \ln CS_{it}$	-0.028		-0.455	0.013		0.258	-0.030		-0.827	0.004		0.077	-0.001		-0.020
	$\ln DE_{it} \cdot \ln NL_{it}$	-0.042		-1.114	-0.082	***	-2.818	-0.046	*	-1.941	-0.052		-1.159	-0.093	***	-3.549
	$\ln DE_{it} \cdot \ln (LPR_{it}/KPR_{it})$	0.100		1.239	0.084		1.279	0.086		1.396	0.162	**	2.035	0.091		1.394
	$\ln CSit \cdot \ln NLit$	-0.050		-0.313	-0.165		-1.528	-0.313	***	-3.947	0.167		1.045	-0.091		-0.781
	$\ln CS_{it} \cdot \ln (LPR_{it}/KPR_{it})$	0.056		0.165	0.051		0.182	-0.263		-1.127	0.013		0.038	-0.004		-0.013
	$\ln NL_{it} \cdot \ln (LPR_{it}/KPR_{it})$	0.057		0.295	-0.212		-1.274	-0.013		-0.099	0.194		0.956	-0.168		-1.050
	SERC	-0.372	***	-5.889	-0.367	***	-7.050	-0.392	***	-9.280	-0.488	***	-7.050	-0.372	***	-7.291
	SPP	0.154	**	2.206	0.152	***	3.101	0.190	***	4.367	0.193	**	2.246	0.213	***	4.049
	WECC	-0.185	***	-2.584	-0.060		-1.071	-0.031		-0.554	-0.178	**	-2.021	0.013		0.202
	NPCC	0.130		0.923	0.106		0.870	0.251	***	3.014	0.163		1.103	0.153		1.299
	RFC	-0.127	*	-1.848	-0.161	***	-2.901	-0.151	***	-4.123	-0.068		-0.783	-0.081		-1.298
	MRO	0.051		0.585	0.060		0.778	0.040		0.680	0.046		0.446	0.145	*	1.909
	ERCOT	0.242	**	2.277	0.235	***	2.849	0.248	***	3.306	0.377	***	3.467	0.236	***	3.081
	t	0.000		-0.033	-0.029	***	-4.097	-0.014	**	-2.533	0.004		0.534	-0.025	***	-3.731

Noise term	ln (σ_v^2)	-1.946	***	-19.879	-1.825	***	-35.791	-2.185	***	-25.317	-1.558	***	-22.185	-1.918	***	-35.928
Inefficiency term (mean)	Intercept							-0.165		-0.966	-4.420		-0.946	-5.525	*	-1.732
	t										-0.338		-1.256	-0.310	*	-1.735
	$TMIN_{it}$										0.125		0.911	0.141		1.353
	$WIND_{it}$										-0.936		-1.080	-1.510		-1.357
	$PRCP_{it}$										7.659		0.425	0.725		0.045
	$TMIN_{it} \cdot COR_i$										-0.117		-0.626	-0.188		-1.086
	$WIND_{it} \cdot COR_i$										0.560		0.414	-1.405		-0.716
	$PRCP_{it} \cdot COR_i$										7.852		0.214	19.679		0.517
	$POSGR_i$										0.077		1.011	0.033		0.069
	$NEGR_i$										0.166		0.363	0.104		0.269
Inefficiency term (variance)	Intercept	-1.261	***	-12.217	-3.871	***	-7.650	-2.767	***	-12.197	-3.984		-0.312	-3.965	***	-8.248
	t				0.285	***	5.860	0.097	***	3.341				0.285	***	6.006
	$TMIN_{it}$				-0.015		-1.245	-0.001		-0.067				-0.013		-1.114
	$WIND_{it}$				0.286		1.618	0.340	**	2.546				0.502	***	2.733
	$PRCP_{it}$				27.643	***	4.001	15.809	***	3.680				29.302	***	4.251
	$TMIN_{it} \cdot COR_i$				0.062	**	2.362	0.037	*	1.868				0.078	***	2.955
	$WIND_{it} \cdot COR_i$				-0.323		-0.831	-0.678	**	-2.238				-0.139		-0.386
	$PRCP_{it} \cdot COR_i$				-23.963	**	-2.178	-38.825	***	-4.227				-30.327	***	-2.682
	$POSGR_i$				0.042	***	3.601	0.071	***	8.647				0.038	***	3.212
	$NEGR_i$				0.029		0.626	0.091	*	1.710				0.025		0.600
	Obs.	402			402			402			402			402		
	Log-likelihood	41.179			78.204			96.772			54.953			105.854		

Significance code: * p<0.1, ** p<0.05, *** p<0.01

Table 4. Significance of variables in the frontier

	Variables	*Log LF*	*D.o.f.*	*LR Test*
	GEM	105.854	-	-
Output Excluded	PL	7.666	6	196.376 ***
	DE	78.116	6	55.476 ***
	CS	98.580	6	14.548 **
	NL	91.307	6	29.094 ***
	GEM (w/o Reg. Dum.)	54.151	-	-
Regional Dummies	NERC	105.854	7	103.406 ***
	RTO	79.782	6	51.261 ***

Significance code: * p<0.1, ** p<0.05, *** p<0.01

Table 5. Modified LCM

Basic LCM (Weather)		
Sample allocation	***Class 1 (No weather variables)***	***Class 2 (With weather variables)***
Number of observations	397	5
Percentage of observations	98.76%	1.24%
Posterior class probability	99.55%	87.81%

Extended LCM (Weather + Weather · COR)		
Sample allocation	***Class 1 (No weather variables)***	***Class 2 (With weather variables)***
Number of observations	397	5
Percentage of observations	98.76%	1.24%
Posterior class probability	98.95%	90.97%

Figure 1. Approaches that allow including environmental variables in efficiency analysis (with key papers)

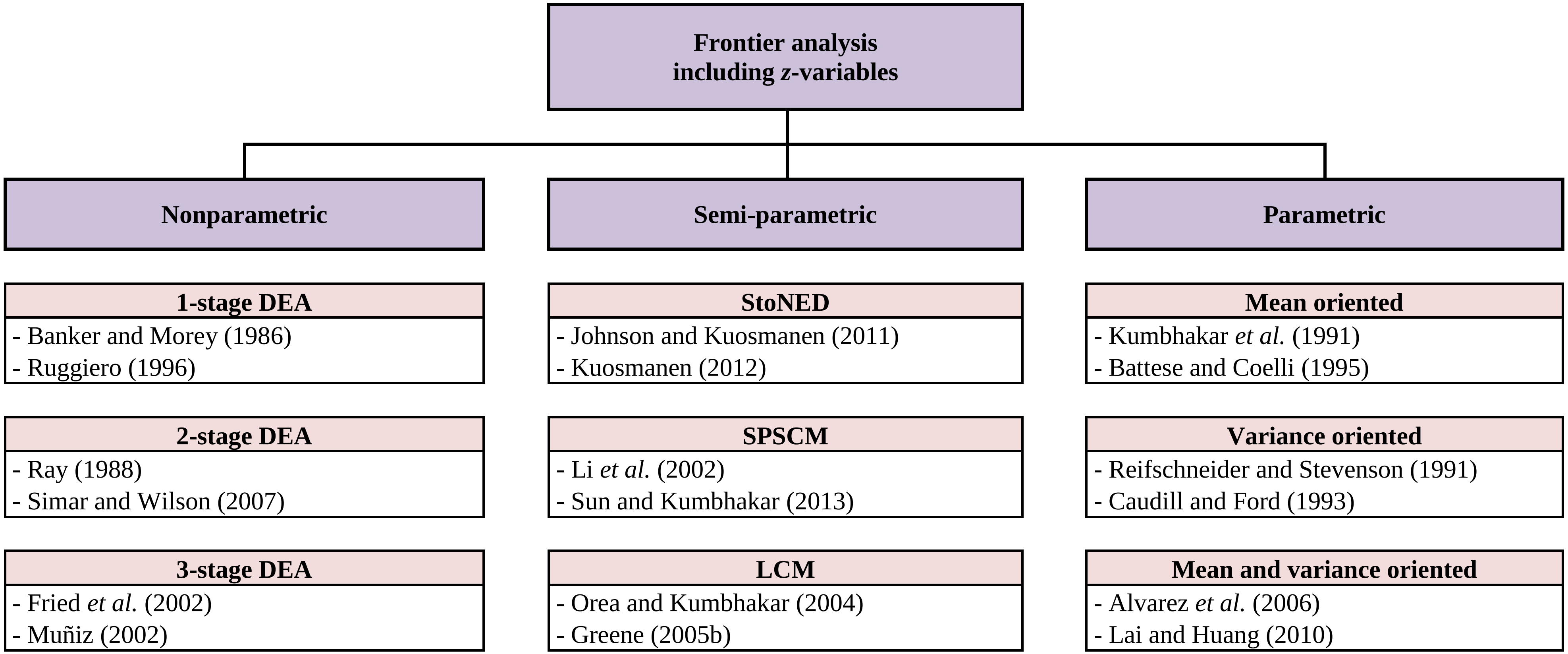


Figure 2. Annual evolution of outputs divided by Totex

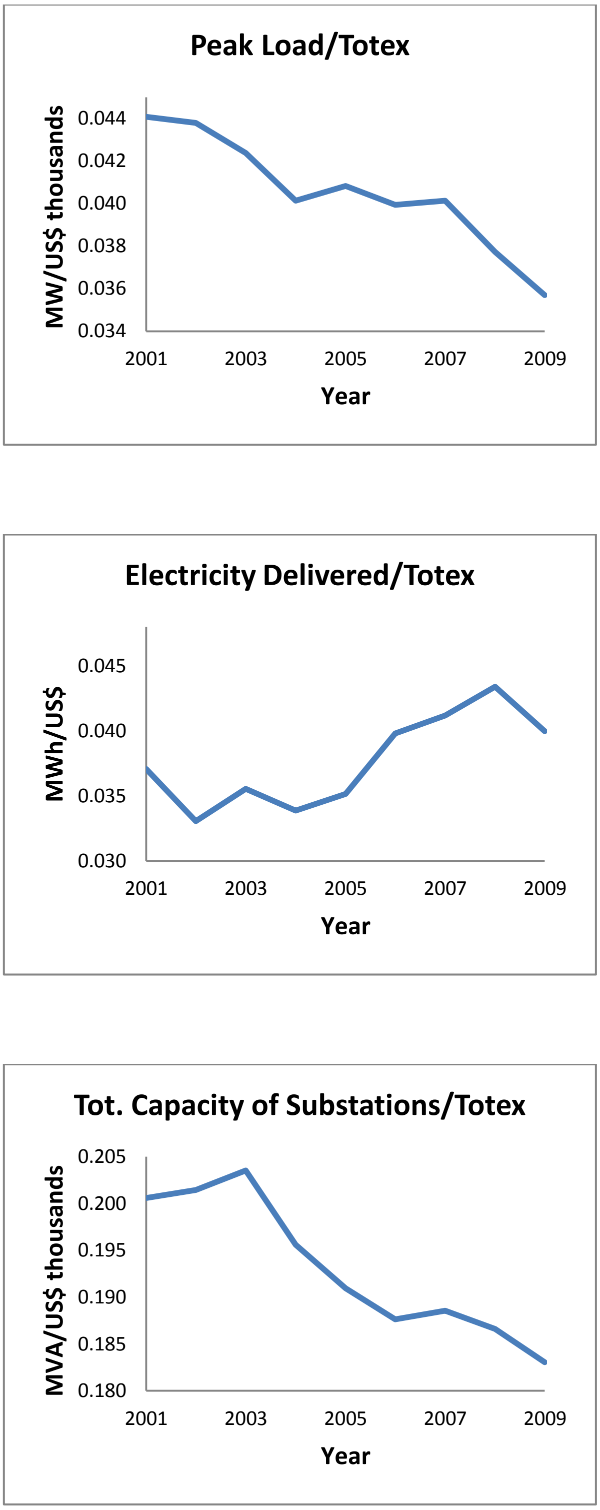


Figure 3. Histogram of efficiency scores for the firms using the GEM

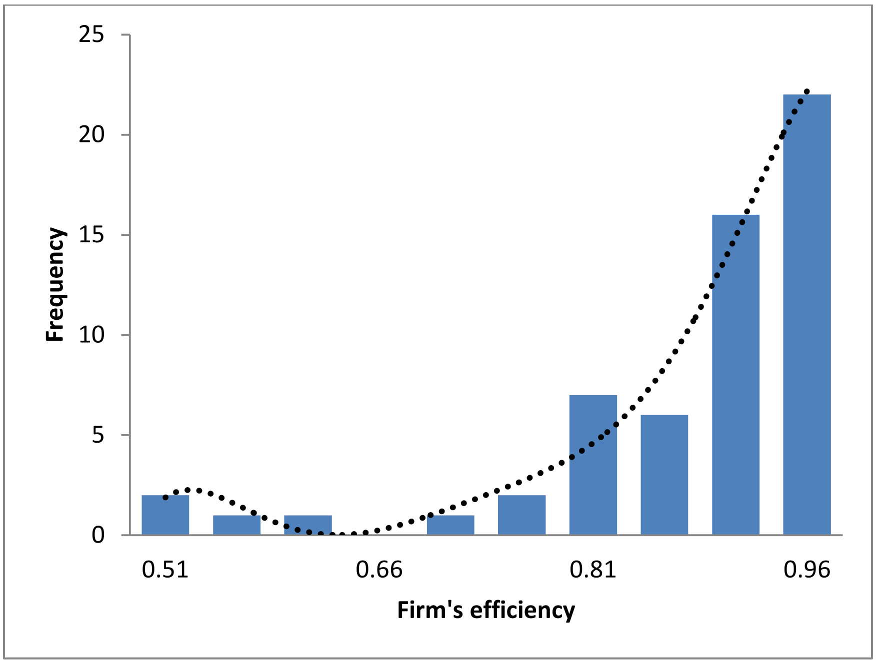


Figure 4. Annual evolution of the efficiency in electric power transmission

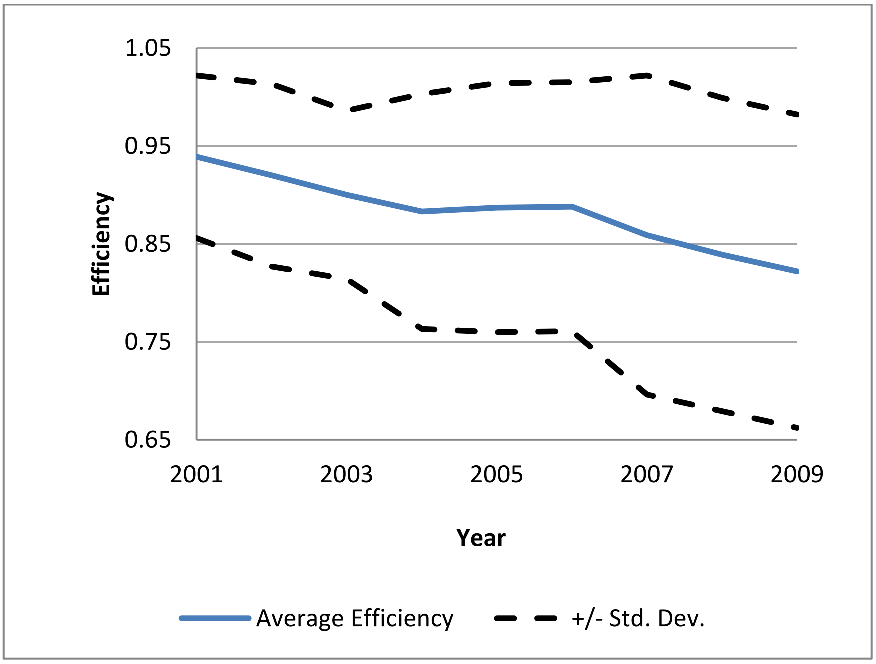


Figure 5. Elasticities of cost for outputs and network

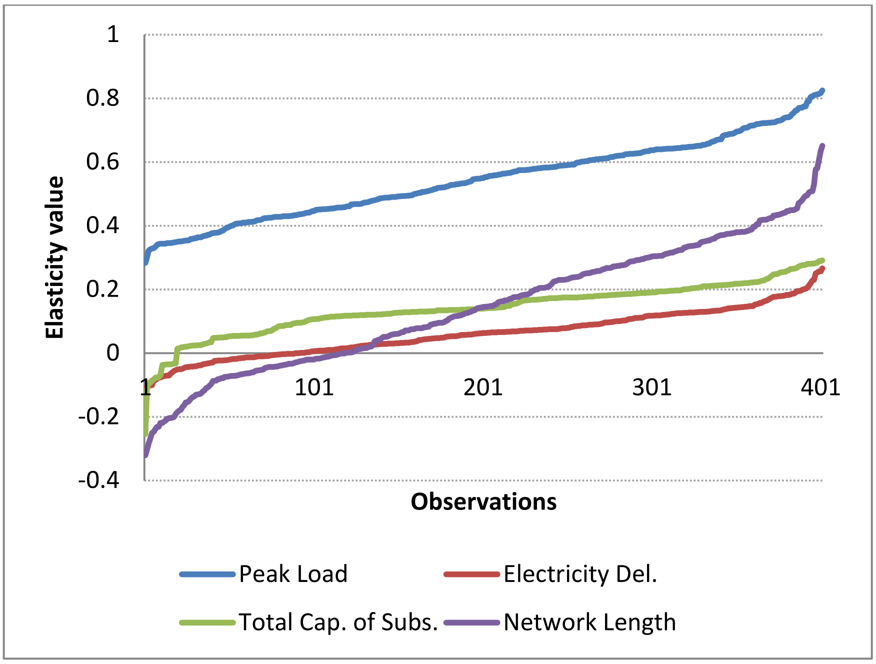
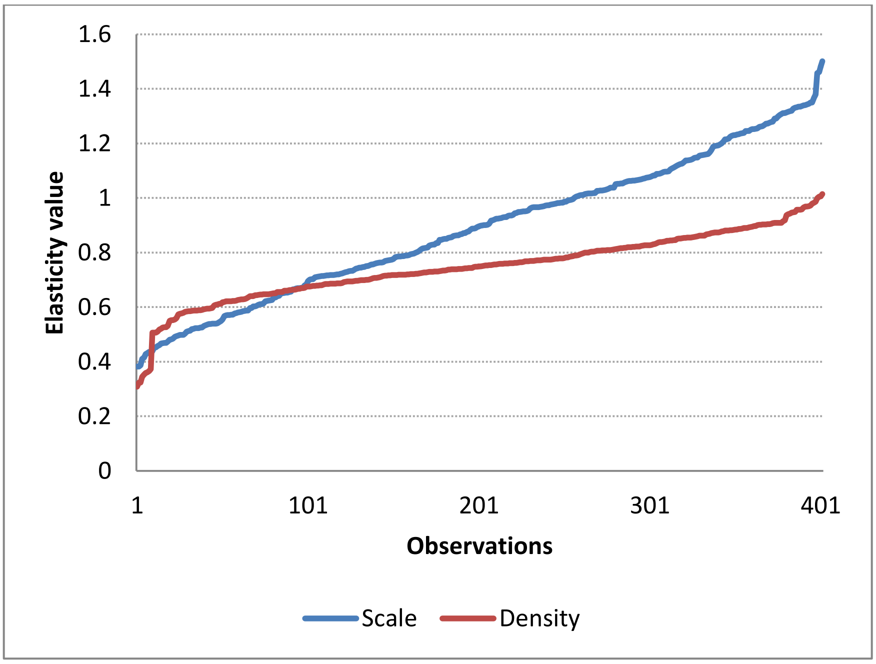


Figure 6. Elasticities of scale and density



APPENDIX

Data Appendix A: Variables and definitions from FERC FORM No. 1

Variable		*Definition*	*FERC pages*	*FERC account names/notes*
	AK	Allocation key (wages)	SWTR / (SWTT-SWAG)	
	SWTR		354-21b	Salaries and wages (transmission)
	SWTT		354-28b	Salaries and wages (total)
	SWAG		354-27b	Salaries and wages (admin. and general)
OPEX		Operational expenditure	100 * (TTE + AK * (TAGE - EPB - RCE - GAE)) / CPI	
	TTE		321-112b	Total transmission (op. and main.) expenses
	TAGE		323-197b	Total administrative and general expenses
	EPB		323-187b	Employee pensions and benefits
	RCE		323-189b	Regulatory commission expenses
	GAE		323-191b	General advertising expenses
CAPEX		Capital expenditure	100 * (DEP + IR * KBAL) / CPI	
	DEP	Depreciation	DETP + AK * (DEPGP + DEPCP)	
	DEPTP		336-7b	Depreciation (transmission plant)
	DEPGP		336-10b	Depreciation (general plant)
	DEPCP		336-11b	Depreciation (common plant)
	KBAL	Capital balance	OCK - ADEP	
	OCK	Original cost of capital	BTP + AK * BGP	
	BTP		207-58g	Balance end of year (total transmission plant)
	BGP		207-99g	Balance end of year (total general plant)
	ADEP	Accumulated depreciation	ADTTP + ADTRP + AK * ADTGP	
	ADTTP		219-25c	Accumulated depreciation total (transmission plant)
	ADTRP		219-27c	Accumulated depreciation total (regional plant)
	ADTGP		219-28c	Accumulated depreciation total (general plant)

TOTEX	Totex	OPEX + CAPEX	
PL	Peak Load	401b	(d) Peak load (MW)
DE	Electricity Delivered	401a-17	(b) MWh (total)
CS	Total Capacity of Substations	427	(f) Capacity of substation in service (MVA)
NL	Network Length	422	(f) + (g) Length of transmission lines (miles)
COR	Capex / Opex	CAPEX / OPEX (average over time for each firm)	
GROWTH	Growth in Demand	[(TE current year - TE previous year) / TE previous year] * 100	

Data Appendix B: Variables from other sources

Variable	***Definition***	***Source***
LPR	Annual Salary	Data Quarterly Census of Employment and Wages (from the US Bureau of Labor Statistics)
KPR	Producer Price Index	US Bureau of Labor Statistics
NERC dummies	Regional dummy variables	North American Electric Reliability Corporation (NERC)
TMIN	Minimum Temperature	National Climatic Data Center (NCDC)
WIND	Average Wind Speed	National Climatic Data Center (NCDC)
PRCP	Average Precipitation	National Climatic Data Center (NCDC)
CPI	Consumer Price Index	International Labour Organisation - LABORSTA (Base Year = 2000)
IR	Interest rate (6%)	Nillesen and Pollitt (2010), p.63